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Beyond cut-points: Accelerometer metrics that capture the physical activity profile

Short title: Capturing the activity intensity distribution

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Abstract

Purpose: Commonly used physical activity metrics tell us little about the intensity distribution across the activity profile. The purpose of this paper is to introduce a metric, the intensity gradient, which can be used in combination with average acceleration (overall activity level) to fully describe the activity profile. **Methods:** 1669 adolescent girls (sample 1) and 295 adults with type 2 diabetes (sample 2) wore a GENEActiv accelerometer on their non-dominant wrist for up to 7-days. Body mass index and percent body fat were assessed in both samples and physical function (grip strength, Short Physical Performance Battery, sit-to-stand repetitions) in sample 2. Physical activity metrics were: average acceleration ($Accel_{AV}$); the intensity gradient ($Intensity_{GRAD}$ from the log-log regression line: 25 m*g* intensity bins (x)/ time accumulated in each bin (y)); total moderate-to-vigorous physical activity (MVPA); and bouted MVPA (sample 2 only). **Results:** Correlations between $Accel_{AV}$ and the $Intensity_{GRAD}$ (r=0.39-0.51) were similar to correlations between $Accel_{AV}$ and bouted MVPA (r=0.48), and substantially lower than between $Accel_{AV}$ and total MVPA ($r \geq 0.93$). The $Intensity_{GRAD}$ was negatively associated with body fatness in sample 1 ($p<0.05$) and positively associated with physical function in sample 2 ($p<0.05$); associations were independent of $Accel_{AV}$ and potential co-variates. In contrast, MVPA was not independently associated with body fatness or physical function. **Conclusion:** $Accel_{AV}$ and the $Intensity_{GRAD}$ provide a complementary description of a person's activity profile, each explaining unique variance, and independently associated with body fatness and/or physical function. Both metrics are appropriate for reporting as standardised measures and suitable for comparison across studies using raw acceleration accelerometers. Concurrent use will facilitate investigation of the relative importance of intensity and volume of activity for a given outcome.

Keywords: intensity gradient; average acceleration; GENEActiv; body fatness; physical function

Introduction

The measurement of physical behaviours with accelerometers that can be worn continually and give access to the raw acceleration data is now widespread. Research-grade accelerometers available, and in use in large global surveys, include the GENEActiv, Axivity and ActiGraph (GT3X+, GT9X/Link) (1-7). Despite the potential to describe the 24-hour (h) physical behaviour profile, output variables derived from accelerometer data are commonly limited to overall activity level and time spent in specific intensity categories such as moderate-to-vigorous physical activity (MVPA) and/or sedentary time.

Overall activity level, defined as average acceleration over a 24 h period, is directly measured and does not rely on population-specific calibration protocols to derive outcome measures; thus average acceleration is comparable across studies and populations. However, it tells us little about the intensity distribution; e.g. it is possible to have a high average acceleration due to a large volume of light intensity activity and relatively little or no MVPA, or due to a substantial amount of MVPA with a large volume of sedentary time. It is important to capture both overall activity and the intensity distribution as, for some health markers and outcomes, it appears the volume of activity is more important than the pattern of intensity (e.g. 8-10), but for others the converse appears to be true (e.g. 11, 12, 13).

Physical activity intensity information is usually expressed as time spent within cut-points that have typically been derived using validation studies. These cut-points are heavily dependent on the calibration sample and the protocol used to derive the cut-points (14, 15), leading to problems comparing outcomes across studies and/or populations (15, 16). Consequently the validity of these outcomes depends not only on the validity of the measure of acceleration, but also on the

validity of the algorithm. A further consideration is average acceleration, time below cut-points (e.g. inactive time), and time above cut-points (e.g. MVPA) are typically highly inter-correlated, suggesting relatively little unique information is obtained from the measures (e.g. as seen in data from 11, 17, 18).

A metric is needed that: captures the intensity distribution; does not rely on calibration protocols (that are, by nature, population and protocol specific); and is more independent of overall activity level, thus can be used alongside average acceleration. The two metrics together would utilise the rich nature of the data available to more fully describe the 24 h physical behaviour profile and, critically, would depend only on the validity of accelerometers at measuring acceleration, rather than also being population or protocol specific.

The purpose of this paper is to introduce a novel metric that describes the intensity distribution of the accelerations experienced over a 24 h period, and can be used in combination with average acceleration to fully describe the activity profile. To demonstrate the potential of the new metric we applied both metrics to two very different data sets: adolescent girls, and adults with type 2 diabetes. Specifically we investigated: 1) whether the intensity gradient was more independent of (i.e. less highly correlated with) average acceleration than MVPA and inactive time; 2) whether independent relationships of overall activity level and the intensity distribution existed with body fatness (adolescent girls and adults with type 2 diabetes), and physical function (adults with type 2 diabetes); and 3) demonstrate how results based on analyses of the directly measured acceleration metrics can be translated to easily interpretable physical activity intensity outcomes post-hoc.

Methods

Sample 1 (Adolescent girls)

Data were obtained from the baseline time-point of the evaluation of the Youth Sports Trust's Girls Active school-based physical activity programme (19). This has been previously described (19), but in brief twenty schools in and on the boundary of Leicestershire and Rutland (UK) took part with approximately 90 girls, aged 11-14 y, invited to participate at random from each school. Parents returned an opt-out consent form if they did not want their child to participate and the girls themselves provided verbal assent. Ethical approval for the evaluation was obtained from the University of Leicester's College of Medicine and Biological Sciences Research Ethics representative, UK.

In brief, the data were collected in measurement sessions run during the school day. Participating girls were requested to wear a GENEActiv accelerometer on their non-dominant wrist (defined as the hand they do not normally write with) 24 h/day for 7-days after the measurement session. Height, sitting height and body mass were measured using standardised procedures. Body mass index (BMI) was calculated and expressed in z-scores of BMI for age according to reference curves for the UK (20). Age was calculated from date of birth to date of measurement, ethnicity was self-reported and later collapsed into categories of White European, South Asian or other, and socioeconomic status (SES) was estimated using the index of multiple deprivation (IMD) from self-reported postcode. Age at peak height velocity (APHV) was calculated as an indicator of biological maturity, and categorised into 'average maturing', 'early maturers' or 'late maturers' (21). Percent body fat was estimated using paediatric bioelectrical impedance scales (Tanita SC-330ST, Tanita Europe BV, Middlesex, UK).

Sample 2 (Adults with type 2 diabetes)

Data were obtained from adult participants (18-75 y) enrolled in the ongoing CODEC study (Chronotype of Patients with Type 2 Diabetes and Effect on Glycaemic Control (Clinical Trial

Registry Number: NCT02973412)). Adults were recruited from both primary and secondary care using direct and opportunistic marketing. Eligible adults were sent an invitation pack containing a patient information leaflet, letter of invitation and reply slip with pre-paid envelope. All participants provided written informed consent. Ethical approval was obtained from the local NHS research ethics committee.

Study data were collected in a single session during the patient's next outpatient appointment unless the patient requested otherwise. The measures relevant to this study were age (from date of birth to date of measurement), ethnicity (self-reported and later collapsed into categories of White (W), South Asian (SA) or other), sex, body mass, height, BMI, percent body fat from bioelectrical impedance scales (Tanita SC-330ST, Tanita Europe BV, Middlesex, UK) and measures of physical function. With the exception of percent body fat and physical function, the above measures were all part of the usual care routine. Physical function measures included:

Handgrip strength (kg): Measured three times in the left and right hand using a digital hand held dynamometer, with the elbow flexed and the forearm in a neutral position. The average of the maximum readings for the left and right hand was taken.

Sit-to-stand 60 test: The number of times a participant could stand from a chair in 60 seconds was recorded.

Short Physical Performance Battery (SPPB): This consisted of chair stands, standing balance and gait speed (detailed below). The SPPB score was the sum of the three tests and could range from 0 to 12 points, with a high score indicating better performance. For details of scoring see Puthoff (22).

Chair stands: The participant started from a seated position on a hard, upright chair, with the feet flat on the floor and the knees bent at 90°. The time taken for the participant to

stand up fully and then return to sitting, without using the hands five times was measured (0-4 points).

Standing balance: This was tested in three progressive positions. If the participant was able to complete 10 seconds in the specified position then the starting position was progressed to the next stage (0-4 points).

- Feet together
- Semi-tandem
- Tandem

Gait speed: The time taken for the participant to walk 2.44 m (8 feet) on a level course was measured (0-4 points).

At the end of the session, participants were given a GENEActiv accelerometer and asked to wear it on their non-dominant wrist (defined as the hand they do not normally write with) 24 h/day for 7-days. They were provided with a pre-paid padded envelope to return the device at the end of the assessment period.

Accelerometer data processing

The GENEActivs were initialised to collect data at 100 Hz and uploaded using GENEActiv PC software version 3.1. The GENEActiv .bin files were analysed with R-package GGIR version 1.2-2 (http://cran.r-project.org) (23, 24). Signal processing in GGIR includes autocalibration using local gravity as a reference (24); detection of sustained abnormally high values; detection of non-wear; and calculation of the average magnitude of dynamic acceleration corrected for gravity (Euclidean Norm minus 1 *g*, ENMO) averaged over 5 s epochs and expressed in milli-gravitational units (m*g*).

Participants were excluded if their accelerometer files showed: post-calibration error greater than

121 0.01 *g* (10 m*g*), fewer than three days of valid wear (defined as ≥16 h per day, Rowlands et al. (17,
122 18)), or wear data wasn't present for each 15 min period of the 24 h cycle. Detection of non-wear
123 has been described in detail previously (See 'Procedure for non-wear detection' in supplementary
124 document to van Hees et al. (23)). Briefly, non-wear is estimated based on the standard deviation
125 and value range of each axis, calculated for 60 min windows with a 15-min sliding window. The
126 window is classified as non-wear if, for at least 2 out of the 3 axes the SD (standard deviation) is
127 less than 13 m*g* or the value range is less than 50 m*g*. The default non-wear setting was used, i.e.
128 invalid data were imputed by the average at similar time-points on different days of the week;
129 therefore the outcome variables were based on the complete 24 h cycle (1440 minutes) for all
130 participants. The distribution of time spent in intensity bins (categories) of 25 mg resolution (0-25,
131 25-50, 50-75…. 4000, >4000) was calculated.

132 Physical activity was expressed as average acceleration across the day (ENMO, m*g*), time
133 accumulated in moderate-to-vigorous physical activity per day (MVPA) and time spent inactive
134 (see below). For each sample, all MVPA outcomes were defined to be consistent with previous
135 research within that population for comparative purposes. For the adolescent girls, $MVPA_{TOTAL}$ was
136 defined as time accumulated above an acceleration of 200 m*g* (25). For the adults, $MVPA_{TOTAL}$ was
137 defined as time accumulated above an acceleration of 125 m*g* as presented in a recent paper using
138 data from UK Biobank (26); $MVPA_{BOUTS}$ was defined as time accumulated in 10-min bouts above an
139 acceleration of 100 m*g* (25), where at least 80% of the bout is above the 100 m*g* threshold as used
140 in previous research (5, 27). Inactive time was defined as time accumulated below 50 m*g* for both
141 samples (17, 28, 29).

142 *Metric to describe intensity distribution across the physical activity profile*

There is a negative curvilinear relationship between intensity and the time accumulated at that intensity, i.e. the total time for all participants is 1440 minutes (24 h), but the vast majority of time is accumulated in the 0-25 m*g* intensity bin, with time accumulated rapidly dropping off as intensity increases and minimal time accumulated at very high intensities, e.g. >1000 m*g*. The nature of the curvilinear relationship for a given participant provides a good descriptor of their physical activity intensity distribution. To describe this curvilinear relationship, for each participant we transformed the curvilinear relationship into a straight-line relationship by taking the natural log of the two wide ranging quantities of intensity and time, i.e. the mid-range of each of the intensity bins (e.g. 0-25 m*g* bin = 12.5 m*g*) and the time accumulated in each intensity bin. We recorded the R^2 (indicative of the goodness of fit of the linear model), gradient and constant of the linear regression equation for each participant. The gradient was always negative reflecting the drop in time accumulated as intensity increases; a higher constant and more negative (lower) gradient reflects a steeper drop with little time accumulated at mid-range and higher intensities (Figure 1a), while a lower constant and less negative (higher) gradient reflects a shallower drop with more time spread across the intensity range (Figure 1b).

Analyses

Descriptive statistics were calculated for each variable using mean (standard deviation) for continuous variables and percentage for categorical variables. Average acceleration was used as the metric for overall activity and the gradient of the participant's log-log linear regression line (intensity gradient) was used as the metric for physical activity distribution.

The two activity metrics were examined and exemplar data plotted to demonstrate how the average acceleration and intensity gradient differed between and within samples. Independent t-tests were used to compare the two activity metrics across samples.

166 *Inter-correlations of activity variables*

167 Pearson's correlation coefficients were used to investigate the inter-correlations between the
168 various activity output variables within each sample to determine whether the intensity gradient
169 was more independent of average acceleration than standard intensity metrics.

170 *Associations between the two activity metrics, body fatness and physical function*

171 Sample 1 (Adolescent girls)

172 To control for clustering at the school level, Generalised Estimating Equations (GEE) were used to
173 determine whether each of the two activity metrics were associated with percent body fat and
174 BMI z-score (dependent variables), (Model 1). Model 2 further controlled for potential co-variates
175 (age, biological maturity, SES and ethnicity), finally Model 3 additionally controlled for the
176 alternate activity metric to test whether associations were independent.

177 Sample 2 (Adults with type 2 diabetes)

178 There was no clustering in this dataset so multiple linear regression analyses were used to assess
179 whether each of the activity metrics were associated with the following dependent variables:
180 percent body fat, BMI, grip strength, sit-to-stand test score and SPPB score (Model 1). Model 2
181 was adjusted for potential co-variates (age, sex, SES, ethnicity and percent body fat (physical
182 function variables only)), and Model 3 additionally for the alternate activity metric to test whether
183 associations were independent.

184 Analyses were repeated replacing the intensity gradient with $MVPA_{TOTAL}$ (both samples) and
185 $MVPA_{BOUTS}$ (sample 2 only). This allowed comparison of results from our new metric, the intensity
186 gradient, to those seen with MVPA metrics.

Continuous variables were centred prior to entry into GEE and regression analyses. The variance inflation factor (VIF) was calculated to check for multicollinearity, a value >5 was taken to indicate the effects of the predictors could not be reliably estimated (30).

Translation of results

Increases in a participant's average acceleration can be made by adding varying durations of physical activity at any intensity greater than the average acceleration. The intensity of the physical activity added will have an impact on the intensity gradient, as it will change the distribution of time across the intensity bins. Whether overall activity, the pattern of activity of both are important for a given health outcome will determine whether an intervention should target the average acceleration (for overall activity), the intensity gradient (for the pattern of activity) or both.

To demonstrate how adding physical activity may impact on average acceleration and the intensity gradient, we determined the time spent in specific activities that would need to be accumulated to increase the overall activity level of participants from samples 1 and 2 by 1 SD. Next we explored the impact on the intensity gradient of each option. We assumed that the introduced activity would replace time spent at the average acceleration. Therefore, for a given activity, the time required is calculated by: 1440 X (increase in average acceleration required by activity at that intensity) / (acceleration associated with that activity – average acceleration). We also show how the recommended activities for a given increase in activity level can be tailored towards a particular balance of intensities. This may be desirable due to the intensity distribution being important for a given health outcome, or to take into account the preferences of a given demographic/individual participant when prescribing or recommending activity.

The representative activities we used to translate the findings from the accelerometer metrics were: pottering/slow walking (approximately 3 km/h), brisk walking (approximately 5 km/h), fast walking (approximately 6.5 km/h, adults only), slow running (approximately 8 km/h) and medium running (approximately 10 km/h). The acceleration values indicative of these activities and used to calculate the time estimates were taken from Hildebrand et al. (25), Phillips et al. (31) and Esliger et al. (32). For the adolescents 100 m*g* was used for pottering/light walking, 200 m*g* for brisk walking, 800 m*g* for slow running and 1000 m*g* for medium running. For the adults 80 m*g* was used for pottering/light walking, 175 m*g* for brisk walking, 400 m*g* for fast walking, 750 m*g* for slow running and 1000 m*g* for medium running.

Results

The descriptive characteristics are presented in Table 1. GENEActiv files were available for 1730 participants in sample 1 and 296 participants in sample 2. Excluded participants totalled 61 for sample 1 (6 failed calibration, 24 incomplete 24 h cycle, 31 fewer than 3-valid days) and 1 for sample 2 (incomplete 24 h cycle), resulting in a final accelerometer sample size of 1669 for sample 1 and 295 for sample 2. All comparable activity measures differed significantly between the two groups, with the adolescent girls (sample 1) having higher average acceleration and intensity gradient, and lower inactive time and regression line constant (intercept). The log-log regression line showed strong linear relationships in both samples ($R^2 > 0.92$, $p < 0.001$), but was significantly higher in the adolescent girls (sample 1).

Figure 2 shows the log-log intensity regression line for a representative participant from each sample. The representative participant from sample 1 (solid circles) has an average acceleration level and intensity gradient that equate to the mean value for each for the sample. Correspondingly, the representative participant from sample 2 (open triangles) has an average

acceleration level and intensity gradient that equate to the mean for each for sample 2. The less active profile of the adult with type 2 diabetes (sample 2, open triangles) can clearly be seen: steeper gradient, lower accumulated accelerations across all but the lowest intensity bin, and the lack of accelerations at the higher intensities. These characteristics are captured by the combination of the two physical activity metrics: acceleration average and intensity gradient.

To demonstrate how the intensity gradient can differ, when the average acceleration does not, a log-log plot for two participants with equally high average acceleration (approximately two SDs above their sample means) is shown in Figure 3a for sample 1 (top left) and Figure 3b for sample 2 (top right). One of the participants in each plot has a steep intensity gradient (approximately 2 SD below their sample mean) and one has a shallow intensity gradient (approximately 2 SD above their sample mean). The same plots for two participants with equally low average acceleration (approximately 2 SD below their sample mean) are shown in Figures 3c for sample 1 (bottom left) and Figure 3d for sample 2 (bottom right). The participants with steeper gradients accumulate more time in low-to-mid range intensities, whereas the participants with the shallower gradients accumulate more time at relatively high intensities. This results in equivalent average acceleration values, within sample.

Inter-correlations of activity variables

Average acceleration was strongly positively associated with $MVPA_{TOTAL}$ in both samples ($r \geq 0.93$, $p < 0.001$), moderately associated with $MVPA_{BOUTS}$ in adults with type 2 diabetes ($r = 0.48$, $p < 0.001$), and strongly negatively associated with inactive time in both samples ($r \leq -0.88$, $p < 0.001$). Correlations between average acceleration and the intensity gradient were still significant, but considerably weaker (sample 1: $r = 0.39$; sample 2: $r = 0.51$; both $p < 0.001$) than for average acceleration with $MVPA_{TOTAL}$ or inactive time, demonstrating the metrics were more independent.

Similarly, correlations between the intensity gradient and $MVPA_{TOTAL}$ (sample 1: r = 0.34; sample 2: r = 0.51; both p < 0.001), $MVPA_{BOUTS}$ (r = 0.29, p < 0.001) and inactive time were all considerably weaker ($r \leq -0.39$ p < 0.001) than the corresponding correlations with average acceleration. All inter-correlations between activity metrics are shown in Supplementary Digital Content (SDC) 1.

Associations between the two activity metrics, body fatness and physical function

Table 2 presents the results of the regression models considering associations of the two physical activity metrics with body fatness (percent body fat and BMI z-score / BMI) in both samples (upper part of Table) and with physical function in sample 2 (lower part of Table). Corresponding results for MVPA are shown in Supplementary Digital Content 2.

Average acceleration and the intensity gradient (Table 2)

Sample 1 (Adolescent girls)

Average acceleration was negatively associated with percent body fat, but not BMI z-score, in the unadjusted model (Model 1, Table 2). The association did not persist after adjusting for co-variates (Models 2 and 3). The intensity gradient was negatively associated with both percent body fat and BMI z-score, with both associations remaining significant after adjusting for co-variates and independent of average acceleration (Models 2 and 3). The VIF was $\leq$1.3 in all cases. An increase of one unit in the intensity gradient was associated with a percent body fat 6.03 percentage points lower and BMI z-score 0.81 units lower. As the size of the 95% CI for the intensity gradient was approximately 0.35, the difference in percent body fat and BMI z-score associated with an intensity gradient at the lower and upper limits of the 95% CI was approximately two percentage points and 0.28 units, respectively.

Sample 2 (Adults with type 2 diabetes)

Average acceleration was negatively associated with both percent body fat and BMI (Model 1, Table 2). These associations persisted after adjusting for co-variates and were independent of intensity gradient (Models 2 and 3). The intensity gradient was significantly negatively associated with percent body fat and BMI in the unadjusted model (Model 1) but only with BMI after adjusting for co-variates (Model 2), and not independent of average acceleration for either percent body fat or BMI (Model 3). The VIF was $\leq$1.4 in all cases. The difference in percent body fat and BMI associated with average acceleration at the lower and upper limits of the 95% CI was approximately two percentage points and 2 $kg.m^{-2}$, respectively.

Average acceleration was not associated with grip strength, but was positively associated with sit-to-stand 60 and SPPB (Model 1, Table 2). These associations remained after adjusting for co-variates (Model 2), but were not independent of intensity gradient (Model 3). The intensity gradient was positively associated with grip strength, sit-to-stand 60, and SPPB Score (Model 1), with all associations remaining significant after adjusting for co-variates (Model 2) and independent of average acceleration (Model 3). The VIF was $\leq$2.1 in all cases. The size of the effect associated with activity levels at the upper and lower ends of the 95% CI for each of the scores was approximately 2.6 kg for grip strength, three extra Sit-to-Stand 60 reps and an SPPB score 0.8 higher (just under half a SD).

Average acceleration and MVPA (SDC2)

Sample 1 (Adolescent girls)

$MVPA_{TOTAL}$ was negatively associated with percent body fat when adjusted for clustering at the school level only, but not after adjusting for co-variates. It was not possible to test for independent effects of MVPA and average acceleration due to multicollinearity (VIFs 10.4-10.5).

Sample 2 (Adults with type 2 diabetes)

$MVPA_{TOTAL}$ was negatively associated with percent body fat and BMI, and positively associated with sit-to-stand 60 and SPPB; these associations persisted after adjusting for co-variates. It was not possible to test for independent effects of $MVPA_{TOTAL}$ and average acceleration due to multicollinearity (VIFs 7.7-8.1).

$MVPA_{BOUTS}$ was negatively associated with percent body fat and BMI, and positively associated with sit-to-stand 60 and SPPB, but only the association with BMI remained after adjusting for co-variates. No independent effects of $MVPA_{BOUTS}$ were evident. The VIF was $\leq$2.1 in all cases.

Translation of results

An increase in the average acceleration level of 1 SD (an increase of 8.7 m*g* and 7.5 m*g* for samples 1 and 2, respectively) could be achieved by replacing time per day spent at the average acceleration level with:

Sample 1:

1) approximately 3 h of pottering around/slow walking OR
2) approximately 75 minutes brisk walking OR
3) approximately 16-17 min of slow running OR
4) approximately 13 min medium running

Sample 2:

1) approximately 3 h of pottering around/slow walking OR
2) approximately 65-70 minutes brisk walking OR
3) approximately 30 min of fast walking OR
4) approximately 15 min slow running OR

5) approximately 11 min medium running

The increase in average acceleration to be obtained from each intensity/activity can be manipulated as long as the sum of the increases is equal to the overall average acceleration increase needed (8.7 mg and 7.5 mg for samples 1 and 2, respectively in the examples). So a combination of activities in a given day can be used to gain the same increase in average acceleration. For example, in sample 2:

6) 1 h of slow walking (2.7 m*g*) AND 30 min of brisk walking (3.2 m*g*) AND 6 min of fast walking (1.6 m*g*), total = 2.7 + 3.2 + 1.6 = 7.5 m*g*.

Or if higher intensity activity was to be emphasised, the same increase in average acceleration could be obtained from:

7) 25 min of slow walking (1.1 m*g*) AND 25 min brisk walking (2.8 m*g*) AND 7-8 min slow running (3.6 m*g*), total = 1.1 + 2.8 + 3.6 = 7.5 m*g*.

All options would increase the average acceleration by the SD of the sample, but the options would have differing impacts on the intensity gradient (note, the impact on the intensity gradient will also depend on the participant's initial activity profile). The effect of each of these on the intensity gradient for a participant from sample 2 (adults with type 2 diabetes) with a low average acceleration and a low intensity gradient (1 SD below the sample mean for each) is depicted in Figure 4. The order of the options reflects the impact on the intensity gradient, with more negative/null effects at the bottom and the most positive effect at the top (exact values for the change in the intensity gradient for our representative participant are in a column in the middle of the plot). The length of the bars represents the total activity time and the patterning of the bars represents the combination of activity types included in the option, the more dense the patterning the more intense the activity. The two lowest intensity options may have a detrimental impact on

345 the intensity gradient (make it steeper) and the more intense the activities selected, the more
346 positive the impact on the intensity gradient (makes it shallower). The same pattern is true for
347 sample 1 (adolescent girls, not shown), but when adding higher intensity activities (slow running
348 or medium running), the effects on the intensity gradient were more pronounced in adults with
349 type 2 diabetes.

350 **Discussion**

351 We have proposed a novel new metric, the intensity gradient, which describes the intensity
352 distribution of the physical activity profile. It is relatively independent of overall activity, in
353 comparison to the intensity variables currently deployed, e.g. MVPA and inactive time. In
354 conjunction with average acceleration (a measure of overall activity level), the two metrics
355 provide a detailed picture of an individual's physical activity profile. Both metrics are calculated
356 from the directly measured acceleration, minimising the error associated with using physical
357 behaviour outcomes that are further removed from the measured variable (33). Neither relies on
358 calibration protocols and therefore both are protocol and population independent, facilitating
359 comparisons between studies and populations (33).

360 We have demonstrated the added value of using the intensity gradient to describe the physical
361 activity profile by investigating relations with body fatness and physical function. The intensity
362 gradient was negatively associated with body fatness in adolescent girls and positively associated
363 with physical function in adults with type 2 diabetes; these associations were independent of
364 overall activity level, as assessed by average acceleration. In contrast, $MVPA_{TOTAL}$ was highly
365 correlated with average acceleration, and $MVPA_{BOUTS}$ was not independently associated with body
366 fatness or physical function. The similarity of the associations between average acceleration and
367 body fatness/physical function with those between MVPA and body fatness/physical function in

Model 2 is not surprising, given the high correlation between average acceleration and MVPA. Given the independent positive associations between the intensity gradient and physical function it is possible that the intensity distribution of the physical activity profile may be of particular relevance to frailty, elderly and/or in rehabilitation. It is likely that for different health and physical function outcomes the relative importance of the average acceleration and the intensity gradient will differ. Use of these two metrics will enable further investigation of independent, additive and interactive effects of activity volume and the intensity distribution on health and physical function. Potentially, this could facilitate the incorporation of choice in physical activity promotion messages, allowing individualisation of interventions.

The average acceleration and intensity gradient metrics are not immediately interpretable in the way that minutes of physical activity are, but translational outcomes can be produced post-hoc using data from calibration studies (e.g. 25, 29, 31, 32, 34). Importantly, this shifts assumptions relating to the conversion of acceleration metrics to physical activity intensity outcomes from the analysis stage to the translation of the research. Further, this means that interpretation and translation can be updated and/or changed with ease by other researchers; access to the primary data would not be required. We have presented an example translation of the outcomes, highlighting how the recommended time accumulated across a range of physical activity intensities per day can be manipulated, e.g. as appropriate for a given health outcome, or as selected as achievable by a participant, or most suited to a given demographic. Translations, such as these could be used to develop meaningful physical activity targets, as appropriate, for individuals or groups. As Wolff-Hughes and colleagues (36, 37) have done for total accelerometer counts per day for US adults and children using NHANES 2003-2006 data, it would also be possible to generate age and sex-specific population-referenced percentiles for both metrics. This would

391 facilitate comparison to norms, comparison of population subgroups (e.g. ethnic groups) and the
392 tracking of physical activity over time (36, 37).

393 Kim et al. (26) recently showed that fatness and grip strength at baseline predicted both average
394 acceleration and total time spent in MVPA at follow-up (median 5.7 y, inter-quartile range 4.9-6.5
395 y) in >93,000 participants in UK Biobank. This is consistent with the cross-sectional associations
396 observed for body fatness in the current study. However, in our smaller dataset, while neither
397 average acceleration nor MVPA were associated with grip strength the intensity gradient was. The
398 size of the UK Biobank sample (2) offers considerable scope for exploring potential health and/or
399 performance differences between participants with similar average acceleration levels but very
400 different intensity distributions. This could feed into whether physical activity interventions and/or
401 public health messages need to focus on volume of activity alone or also on shifting the intensity
402 gradient by focus on specific intensities. We have provided examples of how this could occur in
403 the results section.

404 It should be noted that the validity of the average acceleration and intensity distribution metrics
405 would still be dependent on the procedures used to clean the acceleration signal, e.g. removal of
406 gravity, and detection and treatment of non-wear (23, 24). Furthermore, the magnitude of the
407 intensity gradient will depend on the size of the intensity bins used to summarise the acceleration
408 data. Re-running the analyses with intensity bins of 40 m*g* and 50 m*g* did not change the pattern
409 of the results, but did affect the magnitude the intensity gradient and constant (y-intercept). For
410 consistency, we would recommend standardising the intensity bin size at 25 m*g*. This provides a
411 fairly high, but manageable, resolution.

412 *Strengths and limitations*

413 The current study demonstrates the utility of the proposed metric, the intensity gradient, in two
414 large heterogeneous samples. We only examined data from the GENEActiv accelerometer, but our
415 previous research indicates the same metrics calculated from the Axivity (as used in UK Biobank,
416 Doherty et al. (2)) would likely be equivalent (17). Average acceleration from the ActiGraph (as
417 used in the US National Health and Nutrition Examination Survey (3, 15)) is around 10% lower (17,
418 18), but this appears to be consistent across the intensity range (17, 35) suggesting that the
419 intensity gradient may be comparable.

420 Further, we only used data collected at the non-dominant wrist. Participants in UK Biobank wore
421 accelerometers on their dominant wrist (2), unlike most other studies that use the non-dominant
422 wrist (1, 3-7). Average acceleration tends to be higher when measured at the dominant relative to
423 the non-dominant wrist (unpublished data from our laboratory). Whether the intensity gradient
424 differs will depend on whether or not differences between the dominant and non-dominant wrist
425 are spread equally across the intensity distribution. We plan further research to investigate the
426 degree to which average acceleration and the intensity gradient differ between wrists.

427 In summary, the average acceleration and the intensity gradient together provide a
428 complementary description of a person's entire activity profile and will facilitate investigation of
429 the relative importance of intensity and volume of activity for a given outcome. Crucially, the
430 metrics are not subject to the error and population-specificity associated with converting
431 acceleration into physical activity outcomes. They would be appropriate for reporting as
432 standardised measures, suitable for comparison across the wealth of studies using wrist-worn raw
433 acceleration accelerometers.

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Conflicts of interest and sources of funding

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List of figures

List of Supplemental Digital Content

Table 1. Descriptive characteristics of Sample 1 and Sample 2. Values are mean (standard deviation) for continuous variables and % for categorical variables

		Sample 1 (N=1669) Adolescent girls	Sample 2 (N=295) Adults with type 2 diabetes
Sex	Males	0	60.3
	Females	100	39.7
Age (y)		12.8 (0.8)	63.2(9.7)
Socio-economic status (SES)[a]		5.5(2.9)	6.3(3.0)
Body size	Height (cm)	155.9(8.0)	168.1(10.0)
	Mass (kg)	48.8(12.4)	89.7(17.6)
	Body mass index (BMI) ($kg.m^{-2}$)	19.9(4.0)	31.6(5.3)
	BMI z-score	0.19(1.33)	-
	Percent body fat	24.1(7.7)	35.0(8.5)
Biological maturity	Age at peak height velocity	12.1(0.5)	-
	Early maturer	16.0	-
	On time	68.2	-
	Late maturer	15.8	-
Ethnicity	[b]White	77.3	77.6
	South Asian	11.2	17.2
	Other	11.5	5.2
Physical function	Grip strength (kg)	-	28.5(10.1)
	Sit-to-stand 60	-	22.1(7.8)
	Short Physical Performance Battery (SPPB)	-	9.9(2.0)
*Physical activity	Average acceleration (m*g*)	36.3(8.7)	22.1(7.5)
	[c]$MVPA_{TOTAL}$	45.5(20.4)	42.2(32.8)
	[d]$MVPA_{BOUTS}$	-	9.3(20.4)
	Inactive time (<50 m*g*)	1163.5(53.9)	1240.3(78.3)
*Intensity regression line	Intensity gradient	-2.47 (0.18)	-3.11(0.26)
	Constant	14.7(0.89)	16.8(1.0)
	Variance explained (R^2, %)	95.0(1.8)	92.7(3.3)

[a] SES is measured by the index of multiple deprivation (IMD) 2015 decile score, which ranges from 1-10, where 1 is the least deprived and 10 is the most deprived.
[b]White European for sample 1 and White for sample 2
[c]$MVPA_{TOTAL}$: Total accumulated moderate-to-vigorous physical activity (MVPA) for adolescent girls (>200 mg) and adults with type 2 diabetes (>125 mg)
[d]$MVPA_{BOUTS}$ accumulated in 10-min bouts for adults with type 2 diabetes (>100 mg).
*All physical activity/ intensity regression line metrics different between groups ($p < 0.001$)

Table 2. Associations of the two physical activity metrics with percent body fat (sample 1 and 2) and physical function (Sample 2)

	Model 1		Model 2		Model 3		Independent effect*
	Coefficient	95% CI	Coefficient	95% CI	Coefficient	95% CI	(Model 3)
SAMPLE 1 (Adolescent girls)	Pairwise N= 1527 to 1638		Listwise N = 1521		Listwise N = 1521		
Generalised estimating equations							
Percent body fat							
Average acceleration (m*g*)	**-0.09**	**-0.13, -0.05**	-0.01	-0.05, 0.02	0.03	-0.01, 0.07	X
[a]Intensity gradient	**-9.15**	**-11.46, -6.83**	**-5.58**	**-7.36, -3.81**	**-6.03**	**-7.96, -4.09**	✓
BMI z-score							
Average acceleration (m*g*)	-0.01	-0.01, 0.00	0.01	-0.00, 0.01	**0.01**	**0.00, 0.02**	✓
[a]Intensity gradient	**-1.17**	**-1.53, -0.81**	**-0.66**	**-0.88, -0.44**	**-0.81**	**-1.04, -0.58**	✓
SAMPLE 2 (Adults with type 2 diabetes)	Pairwise N= 260 to 291		Listwise N = 253-279		Listwise N = 253-279		
Multiple regression							
Percent body fat							
Average acceleration (m*g*)	**-0.13**	**-0.26, -0.00**	**-0.15**	**-0.26, -0.05**	**-0.14**	**-0.24, -0.03**	✓
[a]Intensity gradient	**-7.25**	**-10.82, -3.68**	-3.09	-6.34, 0.15	-1.27	-4.55, 2.22	X
BMI (kg.m^{-2})							
Average acceleration (m*g*)	**-0.13**	**-0.21, -0.05**	**-0.15**	**-0.23, -0.08**	**-0.14**	**-0.22, -0.05**	✓
[a]Intensity gradient	**-2.88**	**-5.03, -0.73**	**-2.70**	**-5.09, -0.31**	-0.61	-3.37, 1.78	X
Average grip strength (kg)							
Average acceleration (m*g*)	0.12	-0.03, 0.28	0.09	-0.04, 0.23	0.03	-0.11, 0.17	X
[a]Intensity gradient	**11.09**	**6.63, 15.56**	**4.44**	**0.60, 8.27**	**4.05**	**0.04, 8.06**	✓
Sit-to-stand 60 (repetitions)							
Average acceleration (m*g*))	**0.25**	**0.11, 0.40**	**0.22**	**0.06, 0.38**	0.13	-0.05, 0.30	X
[a]Intensity gradient	**8.83**	**5.83, 11.83**	**7.74**	**4.36, 11.13**	**6.03**	**2.04, 10.02**	✓
Short Physical Performance Battery (SPPB)							
Average acceleration (m*g*)	**0.06**	**0.03, 0.09**	**0.04**	**0.01, 0.07**	0.02	-0.02, 0.05	X
[a]Intensity gradient	**2.19**	**1.44, 2.94**	**1.76**	**1.05, 2.47**	**1.55**	**0.67, 2.44**	✓

[a]Intensity gradient: Gradient of the regression line from log-log plot of intensity (x) and minutes accumulated (y).

Model 1 adjusted for clustering at school level only (sample 1) or unadjusted (sample 2). Model 2 adjusted for potential co-variates. Model 3 further adjusted for alternate activity metric.
95% CI = 95% confidence interval
*The final column indicates whether the associations with each activity metric were independent of the other metric (from Model 3).
Significant associations are denoted in bold.

Supplementary Digital Content 1. Inter-correlations between activity metrics for samples 1 and 2.

Sample	Activity metric	Average acceleration (m*g*)	[a]$MVPA_{TOTAL}$ (min)	[b]$MVPA_{BOUTS}$ (min)	Inactive time (min)
1. Adolescent girls N = 1669	Average acceleration (m*g*)	-	0.95	-	-0.88
	Intensity gradient	0.39	0.34	-	-0.14
2. Adults with type 2 diabetes N = 295	Average acceleration (m*g*)	-	0.93	0.48	-0.94
	Intensity gradient	0.51	0.51	0.29	-0.39

[a]$MVPA_{TOTAL}$: Total accumulated moderate-to-vigorous physical activity (MVPA) for adolescent girls (>200 m*g*) and adults with type 2 diabetes (>125 m*g*)
[b]$MVPA_{BOUTS}$ accumulated in 10-min bouts for adults with type 2 diabetes (>100 m*g*).
All significant $p < 0.001$

Supplementary Digital Content 2: Associations of average acceleration and MVPA with body fatness (Sample 1 and 2) and physical function (Sample 2).

	Model 1		Model 2		Model 3*		Independent effect*
	Coefficient	95% CI	Coefficient	95% CI	Coefficient	95% CI	(Model 3)
SAMPLE 1 (Adolescent girls)	Pairwise N= 1527 to 1638		Listwise N = 1521		Listwise N = 1521		
[a]MVPA$_{TOTAL}$							
Generalised estimating equations							
Percent body fat							
Average acceleration (m*g*)	**-0.09**	**-0.13, -0.05**	0.02	-0.01, 0.06	**-**	**-**	-
[a]MVPA$_{TOTAL}$ (min)	**-0.03**	**-0.05, -0.02**	0.00	-0.01, 0.02	**-**	**-**	-
Body mass index z-score							
Average acceleration (m*g*)	-0.01	-0.01, 0.00	0.01	-0.00, 0.01	**-**	**-**	-
[a]MVPA$_{TOTAL}$ (min)	-0.00	-0.01, 0.00	**0.01**	**0.00, 0.01**	**-**	**-**	-
SAMPLE 2 (Adults with type 2 diabetes)	Pairwise N= 260 to 291		Listwise N = 253-279		Listwise N = 253-279		
[a]MVPA$_{TOTAL}$							
Multiple regression							
Percent body fat							
Average acceleration (m*g*)	**-0.13**	**-0.26, -0.00**	**-0.15**	**-0.26, -0.05**	**-**	**-**	-
[a]MVPA$_{TOTAL}$ (min)	**-0.04**	**-0.06, -0.01**	**-0.04**	**-0.06, -0.15**	**-**	**-**	-
Body mass index (kg.m^{-2})							
Average acceleration (m*g*)	**-0.13**	**-0.21, -0.05**	**-0.15**	**-0.23, -0.08**	**-**	**-**	-
[a]MVPA$_{TOTAL}$ (min)	**-0.03**	**-0.05, -0.01**	**-0.04**	**-0.05, -0.02**	**-**	**-**	-
Average grip strength (kg)							
Average acceleration (m*g*)	0.12	-0.03, 0.28	0.09	-0.04, 0.23	**-**	**-**	-
[a]MVPA$_{TOTAL}$ (min)	0.04	-0.00, 0.08	0.02	-0.02, 0.06	**-**	**-**	-
Sit-to-stand 60 (repetitions)							
Average acceleration (m*g*)	**0.25**	**0.11, 0.40**	**0.22**	**0.06, 0.38**	**-**	**-**	-
[a]MVPA$_{TOTAL}$ (min)	**0.06**	**0.03, 0.10**	**0.06**	**0.02, 0.09**	**-**	**-**	-
Short Physical Performance Battery (SPPB)							

	Model 1		Model 2		Model 3*		Independent effect*
	Coefficient	95% CI	Coefficient	95% CI	Coefficient	95% CI	(Model 3)
Average acceleration (m*g*)	**0.06**	**0.03, 0.09**	**0.04**	**0.01, 0.07**	**-**	**-**	-
[a]$MVPA_{TOTAL}$ (min)	**0.02**	**0.01, 0.02**	**0.01**	**0.00, 0.02**	**-**	**-**	-
[b]$MVPA_{BOUTS}$							
Percent body fat							
Average acceleration (m*g*)	**-0.13**	**-0.26, -0.00**	**-0.15**	**-0.26, -0.05**	-0.12	-0.25, 0.01	X
[b]$MVPA_{BOUTS}$ (min)	**-0.08**	**-0.16, -0.01**	-0.06	-0.12, 0.00	-0.04	-0.10, 0.02	X
Body mass index (kg.m^{-2})							
Average acceleration (m*g*)	**-0.13**	**-0.21, -0.05**	**-0.15**	**-0.23, -0.08**	-0.10	-0.19, 0.00	X
[b]$MVPA_{BOUTS}$ (min)	**-0.05**	**-0.09, -0.01**	**-0.06**	**-0.10, -0.01**	-0.04	-0.08, 0.02	X
Average grip strength (kg)							
Average acceleration (m*g*)	0.12	-0.03, 0.28	0.09	-0.04, 0.23	**0.15**	**0.00, 0.30**	✓
[b]$MVPA_{BOUTS}$ (min)	0.03	-0.05, 0.11	-0.01	-0.07, 0.05	-0.04	-0.10, 0.02	X
Sit-to-stand 60 (repetitions)							
Average acceleration (m*g*)	**0.25**	**0.11, 0.40**	**0.22**	**0.06, 0.38**	0.15	-0.07, 0.37	X
[b]$MVPA_{BOUTS}$ (min)	0.07	-0.02, 0.16	0.07	-0.02, 0.16	0.05	-0.04, 0.14	X
Short Physical Performance Battery (SPPB)							
Average acceleration (m*g*)	**0.06**	**0.03, 0.09**	**0.04**	**0.01, 0.07**	0.04	-0.00, 0.07	X
[b]$MVPA_{BOUTS}$ (min)	0.02	-0.00, 0.03	0.01	-0.00, 0.02	0.00	-0.01, 0.02	X

[a]$MVPA_{TOTAL}$: Total accumulated moderate-to-vigorous physical activity (MVPA) for adolescent girls (>200 m*g*) and adults with type 2 diabetes (>125 m*g*)

[b]$MVPA_{BOUTS}$: MVPA accumulated in 10-min bouts (>100 m*g*).

Model 1 adjusted for clustering at school level only (sample 1) or unadjusted (sample 2). Model 2 adjusted for potential co-variates. Model 3 further adjusted for alternate activity metric.

95% CI = 95% confidence interval

*The final column indicates whether the associations with each activity metric were independent of the other metric (from Model 3). A dash (-) indicates multicollinearity was evident (VIF > 5) preventing the estimation of independent effects.

Significant associations are denoted in bold.

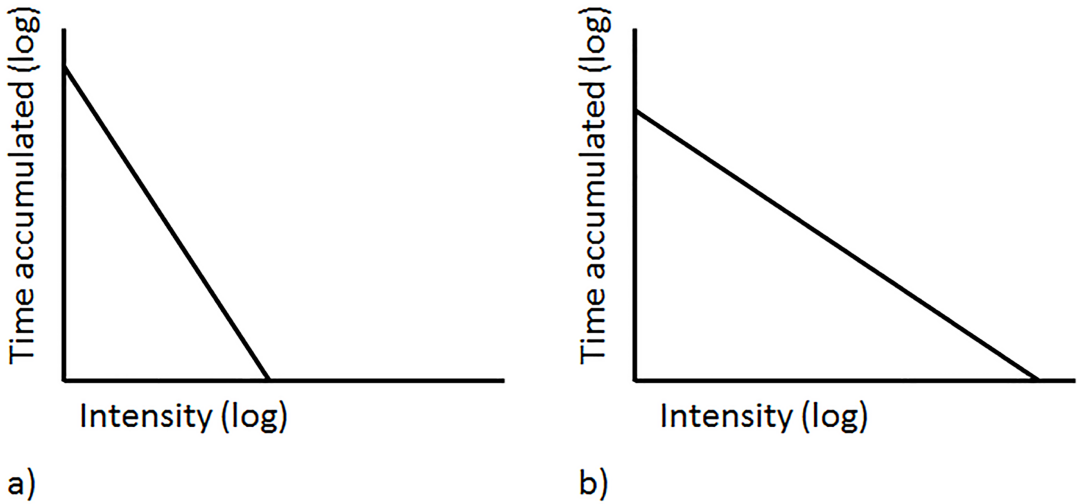

Figure 1: (a) A steeper, more negative (lower) gradient with a higher constant (y-intercept) showing a steep drop in time accumulated with increasing intensity (left) - a poorer intensity profile; (b) a shallower, less negative (higher) gradient with a lower constant (y-intercept) showing more time spread across the intensity range (right) – a better intensity profile.

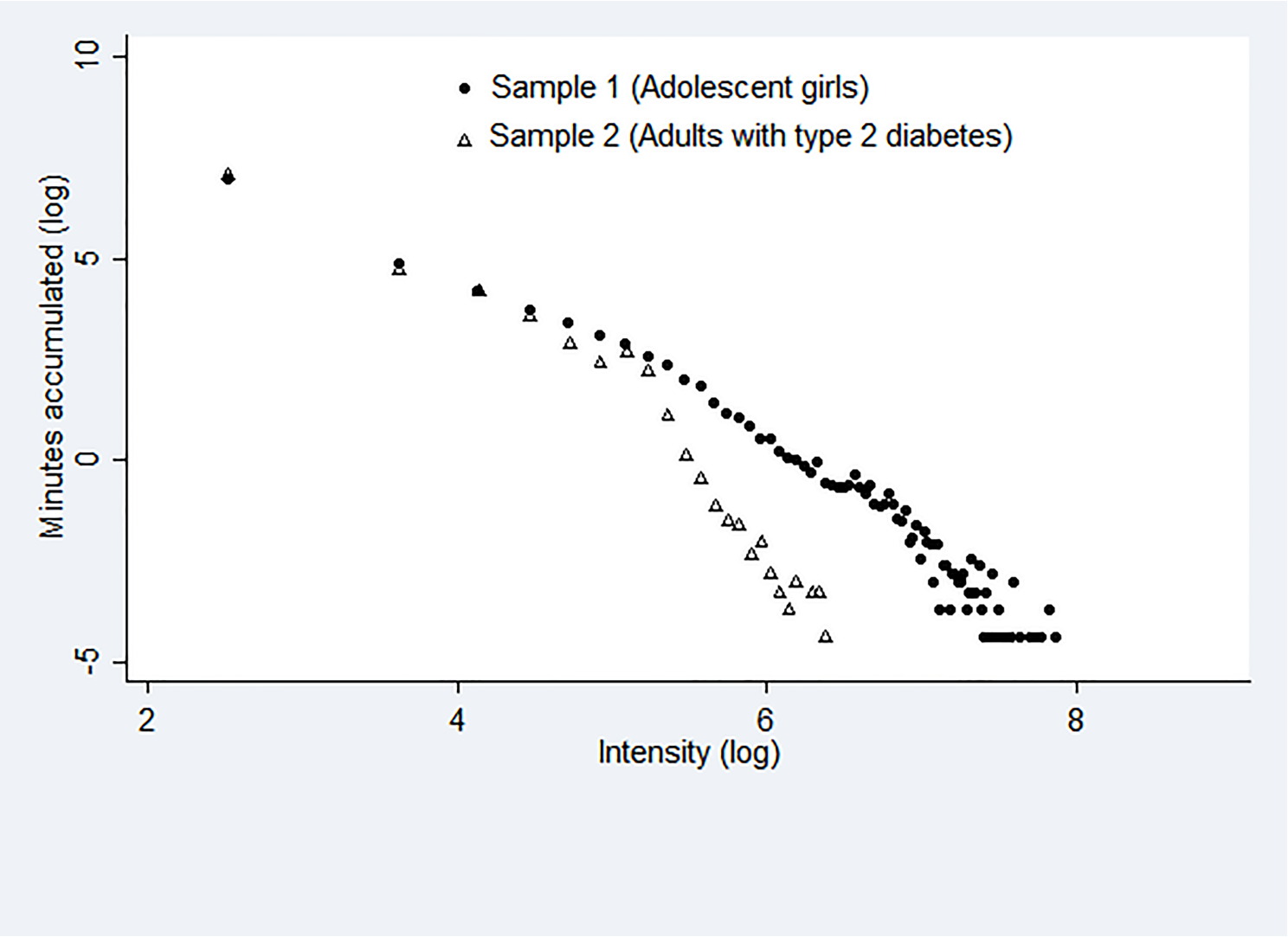

Figure 2. Log-log Intensity regression line for representative participants from sample 1 (solid circles) and sample 2 (open triangles). Both participants have the mean average acceleration and mean intensity gradient for their sample.

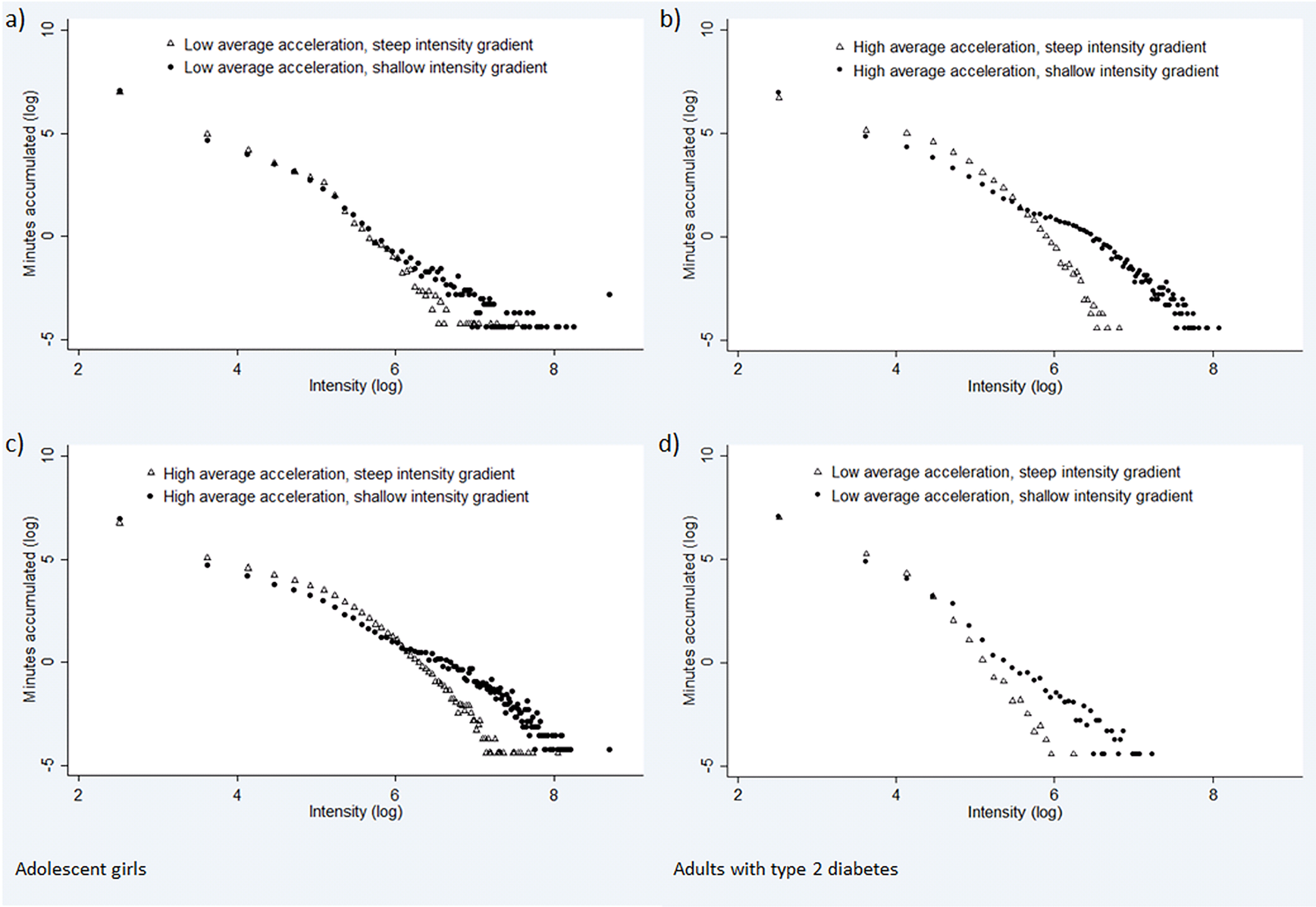
a)
Low average acceleration, steep intensity gradient
Low average acceleration, shallow intensity gradient
Minutes accumulated (log)
Intensity (log)
b)
High average acceleration, steep intensity gradient
High average acceleration, shallow intensity gradient
Minutes accumulated (log)
Intensity (log)
c)
High average acceleration, steep intensity gradient
High average acceleration, shallow intensity gradient
Minutes accumulated (log)
Intensity (log)
d)
Low average acceleration, steep intensity gradient
Low average acceleration, shallow intensity gradient
Minutes accumulated (log)
Intensity (log)
Adolescent girls
Adults with type 2 diabetes

Figure 3. Intensity regression line for representative participants with: high average acceleration and steep (open triangle) or shallow (solid circle) intensity gradients from sample 1 (Figure 3a) and sample 2 (Figure 3b); low average acceleration and steep (open triangle) or shallow (solid circle) intensity gradients from sample 1 (Figure 3c) and sample 2 (Figure 3d). Note average acceleration is similar within each plot. Steep and shallow gradients are similar within each sample (vertically aligned plots).

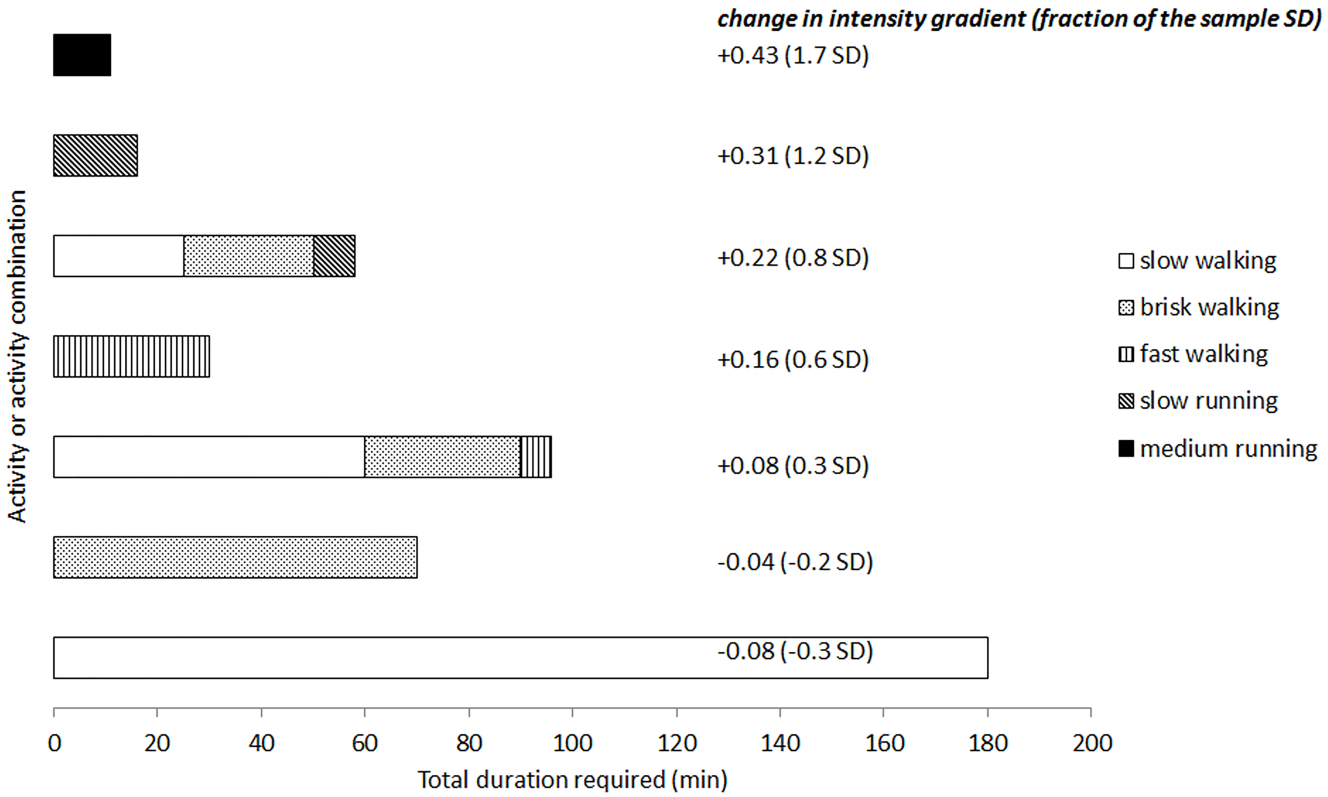

Figure 4. Duration per day of activity type(s), all of which increase the average acceleration by 1 SD (sample 2), and the impact of each on the intensity gradient for an example participant (average acceleration and intensity gradient both 1 SD below sample mean).